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AI ENHANCED VIDEO SEQUENCE ANALYSIS BY WAVELET NEURAL NETWORK WITH RANDOM FOREST

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Abstract

Video-based dance movement recognition technology plays a crucial role in various intelligent applications and finds extensive use in theater industries, particularly in training intelligent dance assistants. This method enables the reconstruction of dancers' postures by extracting features from their images, thereby facilitating the examination and correction of postures to recognize their dance movements accurately. Effective feature extraction is pivotal in this technology, with deep learning emerging as one of the most effective approaches for extracting features from video data. Recognizing specific dance movements is essential for understanding dancer actions and behaviors. However, getting high recognition accuracy is still hard, especially when there aren't many samples and when it's hard to catch the different types of dance activities that happen in space and in the world. To address these challenges and enhance the design of intelligent choreography design and rehearsal optimization, our focus is on machine learning-based dance action recognition model. We use the InceptionV3 pretrained CNN architecture to extract features from the spatial-temporal level of the video data. The modified cuckoo optimisation (MCO) algorithm is then used to choose the best features from a group of options. We also use the wavelet neural network with random forest (WNN-RF) machine learning model to correctly identify dance moves in the video clips. We run tests on a large dance video dataset with 13,400 videos to see how well our proposed model works and how it compares to other methods. This research aims to enhance the efficiency and refinement of choreography design production and provide optimal rehearsal solutions for theater dancers.

Keywords: choreography design, rehearsal optimization, theater dancers, dance action recognition, machine learning

1. Introduction

The extensive usage of network technology and the distribution of information are two examples of how multimedia is a result of contemporary civilization. Multimedia education has become a cutting-edge teaching approach with the development of modern information technology [1]. Inferable from its credits of digitalization, media, extensive data, elevated degrees of commitment, and wide inclusion, it conquers the fleeting and spatial restrictions of customary guidance and gives roads to a more prominent number of individuals to seek after schooling. In the period of sight and sound, dance is a customary work of art that is presently popular. It is an unexpected challenge for dancing and a once-in-a-lifetime opportunity [2].These days, there is a greater diversity in the ways that individuals appreciate art, and science, technology, and futurity have found their way into dance creations. Teaching dance choreography primarily involves instructors imparting dance-related knowledge and abilities in order to motivate pupils to consistently pick up corresponding dance expertise. Teachers and students engage in mutual impact and engagement during this instructional course [3]. In addition to teaching them dancing techniques, we need improve their theoretical understanding of the industry and their capacity for appreciating music in order to develop skilled choreographers. In addition to having a high level of creative achievement, a dancer should be exceptionally skilled [4].

The production and distribution of art had a significant evolution and eventually became linked to multimedia under the impact of multimedia background [5]. Multimedia encourages the dissemination of art, which helps the once relatively narrow art categories move toward the mass market. The integration of multimedia teaching tools into dance choreography courses can facilitate the seamless flow of learning activities and present pertinent dance knowledge and skills to students in an engaging manner [6].Simultaneously, it has the potential to infuse contemporary dance creation with fresh energy and support the development of dance image, language organization, segment arrangement, and other connections [7]. In multimedia teaching, managers use various techniques and contemporary educational theories in addition to following the teaching principles, planning and organizing

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instructional activities, adopting multimedia technology, allocating and utilizing instructional resources logically, and keeping students in mind [8].In the context of computer network, this is done in an effort to meet optimal teaching objectives. Advanced teaching theory must serve as a guide for the successful integration of multimedia technologies and dance course instruction, just as it does for other disciplines. As PC innovation has progressed, individuals have made an assortment of machine learning (ML) calculations that make dance moves by powerfully assembling information [9]. Moving developments are additionally produced by the hidden Markova model (HMM). A various leveled Gee with nonparametric result thickness, the non-boundary progressive system stowed away Markov model (NPHHMM) was first presented in 2005 [10]. The development of repeatable movement motors for gaining and human engine capacities can profit from the use of this idea.

Utilizing the gathered acoustic and semantic parts of human language, a few scientists have likewise investigated coordinating sound examination with text [11] and have fostered a method for producing 3D virtual people from sound data [12]. Head developments, binocular saccades, motions, flickers, and looks are instances of distinctive virtual looks and elements that are made by breaking down the mood of hear-able data and interfacing it with related lexical implications [13].The analysts confirmed the way that their calculation is obviously better than traditional calculations that make virtual people exclusively through discourse mood [14]. Head developments, binocular saccades, signals, flickers, and looks are instances of striking virtual looks and elements that are made by dissecting the mood of hear-able data and interfacing it with related lexical implications [15][16]. The analysts confirmed the way that their calculation is much better than regular calculations that make virtual people exclusively through discourse beat [17]. The strategy for recreating the material science of a moving human body and giving it qualities that it would have in the genuine world, like flexibility, and grinding, is known as physical science based practical person liveliness [18]. These characteristics utilized to determine a character's state of motion at a subsequent time step, thereby providing the character's whole motion, given their current state of motion. To get a more realistic outcome, the designer must optimize the motion model by changing the physics algorithm's settings [19]. Both the piece flower combination and the handkerchief flower combination have dances that are comparable. A controller is a type of physics model derivation, and each controller corresponds to a specific movement behaviour. For example, the walking controller starts with a walking state and uses math to make a model of how the character walks [20].

Our contributions. Our focus is on an ML-based dance action recognition model that will improve the design of intelligent choreography and rehearsal optimization. The subsequent principal contributions integral to the proposed work.

1. The study enhances the field by utilizing the InceptionV3 pretrained model to extract deep features from video data. InceptionV3's complex structure makes it possible to get spatial-temporal features from dance sequences, which show how body parts move in complex ways and how they relate to each other in space.

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2. The use of the modified cuckoo optimization (MCO) algorithm is a new way to choose features for recognizing dance actions. MCO successfully traverses the high-dimensional feature space to pinpoint the most discriminative features, thereby augmenting the model's resilience to noise and extraneous data.
3. The combination of the wavelet neural network (WNN) and the random forest (RF) is a complex way to learn that is well-suited to the challenges of recognizing dance actions. WNN-RF allows the model to accurately capture both short-term and long-term temporal dependencies in dance movements, which improves recognition performance.
4. The research adds to the field by doing a lot of tests with a large dance video dataset that has 13,400 videos. By systematically evaluating the model's accuracy, robustness, and generalization capabilities, the research provides valuable insights into its effectiveness and applicability in real-world scenarios.

The rest of this paper is organized as follows. In Section 2, we present a thorough review of the existing literature concerning the intelligent choreography design and rehearsal optimization. Section 3 delves into the research methodologies and principles employed in this study, including the ML techniques. Moving forward, Section 4 conducts comparative analysis and provides a comprehensive assessment of the prediction outcomes using various metrics. In Section 5, the conclusions and expectations of this research are discussed.

2. Review of literature

2.1 State-of-art works

The examination for the most part [21] centers around the programmed arrangement of nonstop movement by utilizing the profound learning approach to raise the improvement level of canny dance training and movement network innovation. It tackles the mechanical test that old style movement's dynamic division and cycle division of the programmed age design can't achieve worldwide improvement. It is design for start to finish persistent dance documentation that is consequently produced and gives fleeting classifier access. Analyzes at long last presume that superior exhibition development time-stepping is effectively accomplished by the model. Moreover, it empowers the complex production of nonstop movement with worldwide movement identification when matched with consistent movement acknowledgment innovation, checking movement length simultaneously.

The research [22] generally centers around the programmed arrangement of ceaseless movement by utilizing the profound learning approach to raise the improvement level of canny dance training and movement network innovation. For outline bunching, a unique time-stepping model is made in view of this. Analyzes at long last presume that superior exhibition development time-stepping is effectively accomplished by the model. Moreover, it empowers the complex production of nonstop movement with worldwide movement identification when matched with consistent movement acknowledgment innovation, checking movement length simultaneously. This examination gives progressed specialized means to choreographic instruction, significant experience for school network movement

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training, and a viable approach to understanding the refined and productive making of computerized ceaseless movement.

Folk dances [23] are passed down and preserved in large part because to the popular Labanotation dance recording method. It takes time and effort to draw dancing notation by hand. This article suggests a way for automatically creating Labanotation using motion capture data. BVH-organized Euler point information is changed into a succession of the 3D Cartesian world directions as per the investigation of human unresolved issues the calculation of the bowing point and movement include groupings more straightforward. It is suggested that a movement division procedure break down different types of movement into smaller parts so they are easier to recognize. This method is based on the properties and rhythms of kinematics.

Augment Reality, [24] or AR, is a new technology that blends simulation with computer technology. Because AR is multi-perceptual, interactive, immersive, and many other qualities, it can mimic the real world and deliver it to users in a way that creates an immersive experience. The equivalent can be applied to sports dance to work on the effect of guidance and learning by means of increased reality innovation. To resolve the issues of idleness and energy utilization of terminal gear coming about because of fast information transmission and virtual innovation calculation, this research suggests a transmission system for sports dance developments that uses equivalent power conveyance on the uplink. A numerical mobile edge computing (MEC) in view of curved improvement is laid out, gave that the power utilization and postpone meet the imperatives. The trial findings demonstrate the effectiveness of the suggested AR and MEC-based sports dance movement evaluation approach.

After publication [25], remarkable equals were found between this unique issue exposition and recently delivered materials. There is proof that endeavors have been made to utilize programmed rework to conceal the replicating. Following the endorsement of these exceptional issue papers by the visitor manager in control by an examination was led to see whether the Unique Issue's trustworthiness and thoroughness of the companion survey process elevated requirements. Regretfully, these papers were not sent to the designated Handling Editors or the Editor in Chief for approval in accordance with the journal's regular workflow because of a configuration issue in the editorial system.

The idea that [26] physical activity encourages good aging is widely acknowledged. Although there are many different dance styles and techniques, and there are still few robust study designs for intervention studies, recent research indicates that dance may help improve seniors' physical and mental health. A randomized, open-label, single-center experiment with parallel assignment and 62 elderly participants was carried out using volunteers from the community. AET, DMT, or the control group was randomly allocated to receive a 12-week of instruction. Assessments were conducted on health-related quality of life, physical fitness, and cognitive functioning at baseline (T-0) and after training (T-12 weeks).

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Since July 2007, [27] a network of tilt meters, or vertical static pendulums, has been in use throughout Central Europe. Over the 10 years, there have been 183 seismic occurrences with a magnitude of seven or higher recorded globally (EMSC). Before the main shocks, a number of tilt anomalies were identified in a matter of days to months. The most common anomaly was an abrupt tilt where the pendulum was mounted, parallel to the underlying geologic structure. We are putting forth an asperity model based on the observations, which explains the production of "stress waves" prior to the main shocks. These extremely low frequency stress waves, which last for days to months, can be found all over the world, but they are most common on active geological formations that run parallel to the fault where a main shock occurs. According to the observations, we may be able to estimate the portion of the global fault system that produces the stress wave that is detected and that eventually reaches the critical condition. The magnitude of the main shock may be estimated based on the tilt amplitude and the length of the stress wave (its period).

A popular [28] notation method for recording dances is called Labanotation. A few procedures have been put on a mission to naturally create Labanotation from movement catch information to lessen work expenses and time. They offered a hearty and proficient Labanotation age model utilizing a combination include based CRNN-based consideration seq2seq model. To extricate the overall calculation connections between associated bones as well as the data about the bones between adjacent joints, we first breaker the bone element and the Untruth bunch include. The consideration component is sued to learn great arrangements between input movement highlight successions and result image groupings, and CRNN to get familiar with the spatial-fleeting portrayal of movement catch information in the proposed seq2seq model.

To determine whether [29] dance aerobics is a useful tool for improving female students' motor activity and psychophysical status. Descriptive and comparative statistical approaches were used to process all of the study's data. From the graphic measurements space, the resulting boundaries were laid out: normal focal and dispersive boundaries, including start and last estimating, standard deviation, and number juggling normal. To think about the number-crunching method for two free informational collections and an unpaired test was utilized in similar measurements.

The teaching of music and dance courses to college students is receiving an increasing amount of attention in the curriculum setting process. This subject is still taught in a traditional manner, with less emphasis placed on the practical activities that students complete. Upon examining the textbooks chosen by numerous colleges and institutions for their music dance courses, it becomes obvious that most of them actually focuses on coordinating specific activities from the viewpoint of music dance majors, and don't have a primary comprehension of the educational program. They presents a few explicit thoughts for establishing a remote learning climate [30] for music dance courses in light of the ongoing school educational plan framework setting and looks at the one of a kind conditions of the far off music dance schooling system by analyzing relevant AI information.

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2.2 Problem description

Dance datasets frequently exhibit constrained sample sizes, complicating the training of resilient machine learning models capable of generalizing effectively to novel data. This limitation hampers the accuracy and reliability of dance action recognition systems. Dance movements exhibit intricate spatial and temporal variations, which pose significant challenges for traditional recognition methods. Capturing the nuances of these variations requires sophisticated techniques capable of processing both spatial and temporal information effectively [31]. Choreography design requires effective tools and methods for analyzing and improving dance movements. Current methods might not be precise or scalable enough to make choreographic workflows more efficient. Rehearsals are very important for improving dance performances and making sure that all the dancers are in sync. But it's still hard to make rehearsal schedules and plans that work best for everyone. The theatre dance industry needs smart solutions that can help with making choreography, making rehearsals more efficient, and improving performances. Current technologies might not be able to meet these specific needs of the theatre dance industry, which shows that new methods are needed that are specific to theatre dance productions.

1. Create a machine learning model that can accurately identify complex dance moves shown in video sequences by using advanced deep learning methods and feature extraction algorithms.

2. Research and improve methods for extracting features, with an emphasis on getting deep features and using smart feature selection algorithms to improve the model's recognition performance while reducing noise and redundancy.

3. Use a large dance video dataset to do thorough tests of the model's performance metrics across a range of dance genres, styles, and performers to make sure it is strong and can be used in a variety of situations.

4. Make useful tools and solutions that make it easier to plan choreography and make the most of rehearsal time in theatre dance productions. This will give choreographers and production teams more information from accurate dance action recognition.

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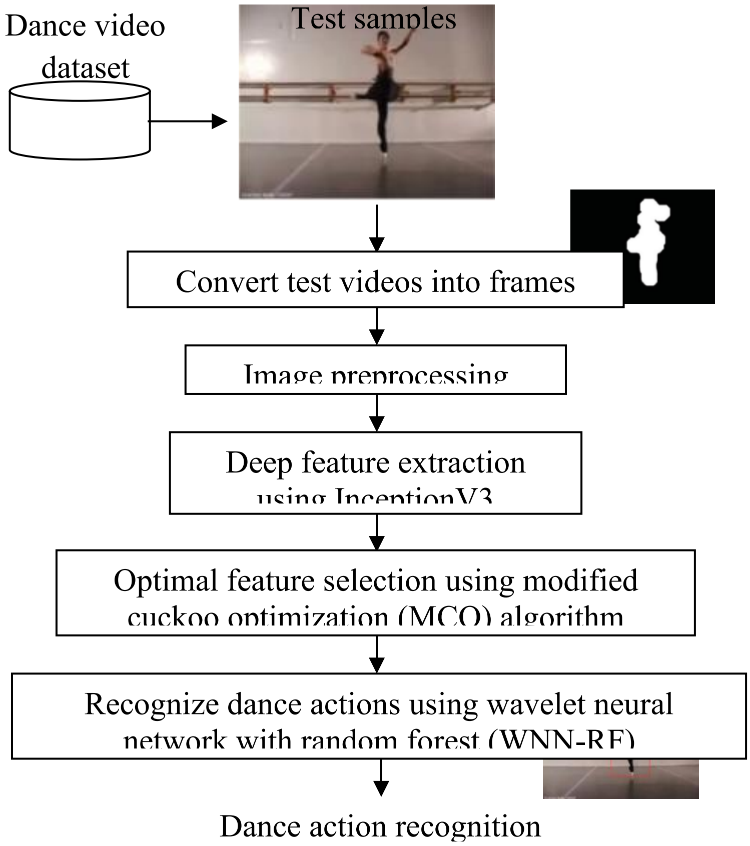

Fig. 1 Dance action recognition for intelligent choreography design and rehearsal optimization

3. Proposed methodology

The intelligent choreography design and rehearsal optimization for the dance action recognition model is created using a methodical process that includes several important steps, as seen in Fig. 1. The research project starts with a large dance video dataset that has 13,400 videos. We choose certain test samples from this dataset to use for testing. These test samples are turned into separate frames so that dance actions can be analyzed at the frame level. After that, the frames go through image preprocessing methods that are meant to improve their quality and make sure that the dataset is consistent. The essential process of deep feature extraction is executed through the robust InceptionV3 convolutional neural network architecture, recognized for its effectiveness in image classification tasks. The modified cuckoo optimization (MCO) algorithm is used for optimal feature selection to improve the feature space and reduce redundancy. This step makes sure that only the most important and useful features are kept for later analysis. The dance action recognition phase is the most important part of the model. This is where the best features are put into a hybrid model that includes a wavelet neural network (WNN) and a random forest (RF) classifier. This hybrid method can find both spatial and temporal dependencies in the dance sequences, which makes it easier to correctly group different dance moves [33]. Lastly, the model outputs the

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dance actions it has recognized, which gives useful information about how to design choreography and make rehearsals more effective. This method uses advanced deep learning methods and optimization algorithms to make an intelligent system that can accurately and reliably recognize dance moves.

3.1 Feature extraction

InceptionV3, a convolutional neural network (CNN) architecture created by Google, is known for its advanced design that is ideal for extracting features from images. The architecture's technical details, such as its depth, inception modules, and extra classifiers, make it good at finding complex visual patterns and hierarchies of features. InceptionV3 is made up of many layers of convolutional, pooling, and fully connected units that are arranged in a deep and complex way. The main new thing about it is its inception modules, which let different kernel sizes do parallel convolutional operations in the same layer. This lets the network efficiently pick up features at different spatial scales, which lets it see both fine-grained details and broader contextual information in images. One of the best things about InceptionV3 is that it was trained on big image datasets like ImageNet before it was released. The network learns to pull out general visual features during pre-training by changing its parameters to make sure that it makes as few classification mistakes as possible across a wide range of image categories. In the context of dance action recognition, InceptionV3 acts as a feature extractor by analysing video frames and pulling out high-level representations of the spatial and temporal patterns that are part of dance movements.

1. Change unprocessed video data into a series of RGB frames with the same size and format. Use methods like resizing, cropping, and colour normalization to make the frames all the same size so they can be processed the same way every time.

2. Use the InceptionV3 architecture, which has convolutional and pooling layers with inception modules, to get deep features. Pass each frame through the network and get feature representations from the middle layers while keeping spatial and temporal information.

3. Combine frame-level features into a small representation for the whole video sequence. Use methods like max pooling, average pooling, or RNNs to combine features from different frames while keeping the time dynamics.

4. Normalize the features you got so that they are centred on a mean of zero and a variance of one. This makes them less sensitive to changes in input distributions. Use feature scaling techniques such as min-max scaling or feature-wise normalization to make sure that the ranges of features are the same across all dimensions.

5. Combine the normalized features with classification models that can recognize dance actions. Use the extracted features to train models like support vector machines (SVMs), recurrent neural networks (RNNs), or convolutional neural networks (CNNs) to learn how to connect feature representations with the dance moves that go with them.

By carefully following these technical steps, practitioners can use InceptionV3 to extract features from dance action recognition. It lets you get high-dimensional, semantically rich

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features that show how dance movements change over time and space in a complicated way. This is the basis for accurate and strong classification models.

3.2 Optimal feature selection

Choosing the best features is an important part of building machine learning models, especially when the feature space is very large or has features that aren't needed or are redundant. Finding the most discriminative features can make the model much more accurate and efficient when it comes to recognizing dance actions. The modified cuckoo optimization (MCO) algorithm provides an advanced methodology to address this issue by effectively navigating the feature space and identifying the most pertinent feature subsets.

- The MCO algorithm efficiently explores the feature space by simulating the behaviour of cuckoo birds. This lets it find potentially optimal subsets of features for the task at hand.
- Each subset of features is evaluated based on a fitness function, which measures how well it improves model performance for dance action recognition.
- MCO uses things like destroying and rebuilding nests to keep updating feature subsets, replacing less useful ones with better ones over time.
- The algorithm fosters diversity within the feature subsets by generating new solutions (eggs) and allowing them to compete with existing subsets, ensuring adaptability and exploration of the feature space.
- Through iterations of exploration and selection, the MCO algorithm converges toward optimal or near-optimal feature subsets that contribute to accurate and efficient dance action recognition models.

An example cluster is characterized as the accompanying capability.

$$Habitat = [m_1, m_2, ... m_{B\,\mathrm{var}}] \quad (1)$$

The appropriateness of current natural surroundings accomplishes by (F_n) benefit capability in living space. As indicated by the accompanying condition:

$$profit = F_n(Habitat) = F_n[m_1, m_2, ... m_{B\,\mathrm{var}}] \quad (2)$$

MCO is a calculation that boosts the advantage capability. To involve MCO for Minimization critical thinking, it is adequate to duplicate a negative imprint in cost capability, as per the accompanying condition:

$$profit = -\cos t(Habitat) = F_c[m_1, m_2, ... m_{B\,\mathrm{var}}] \quad (3)$$

To begin improvement calculation, a lattice with Bpop × Bvar is made and afterward foreach territory, haphazardly egg doles out. In nature, each cuckoo lays from 5 to 20 eggs. So each cuckoo has an upper and a lower limit for egg laying at various emphasess. One more territory of genuine cuckoos is that they lay eggs inside a greatest separation from their environment. This most extreme reach is be classified "Egg Laying Range (ELR)". In an advancement issue with furthest constraint of and lower cutoff of for factors, each cuckoo has an ELR which is relative to the complete number of eggs; number of current cuckoo's eggs

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and furthermore factor cutoff points of and . The ELR is characterized as in the accompanying condition:

$$Elr = \alpha \times \frac{No\ \ of\ current\ cukod's\ \ eggs}{All\,no\ \ of\ \ eggs} \times (Var_{ih} - Var_{Low}) \tag{4}$$

where α is a number, expected to deal with the most extreme worth of ELR. Prior to inspecting how to discrete MCO for diagram shading issue, first we examine the reason why picking discrete technique. Each cuckoo in view of its benefit worth can lay various eggs (B_{egg}) which is an irregular number as follows.

$$B_{egg} = W_h \left(\frac{F_h}{F_{best}} \right) \tag{5}$$

where and Legg and Uegg are utilized as the upper and lower cutoff points of egg commitment to each cuckoo at various cycles, separately. The goal capability is corresponding to the size of arrangement in the thought about issue and the complete number of eggs, and number of considering cuckoo's eggs and another unique controlling boundary αitr as follows:

$$delr = \alpha_{itr} \cdot b \cdot \frac{B_{egg}}{SB_{egg}} \tag{6}$$

where α_{itr} is a boundary to control the worth of DELR. The bigger α_{itr} is, the better the worldwide advancement ability will be. This implies α_{itr} will be progressively diminished throughout an opportunity to get better assembly or heightening of IDMCO in last developments and more enhancement in mid ones. A straight changing system like the cooling capability in reproduced tempering, i.e., α_{itr} is gotten in every development as follows.

$$\alpha_{itr} = \alpha_{\max} - B_{itr} \frac{(\alpha_{\max} - \alpha_{\min})}{SB_{itr}} \tag{7}$$

where αmin and αmax are characterized as the base and greatest constraints of αitr during the IDMCO, individually. Additionally, B_{itr} and SB_{itr} recognize the emphasis number whose is processed and the complete number of α_{itr} emphasess, individually. As such, to get the distinction between two vectors in a discrete space, rundown of important movements to change from to , entitled that acquires through component changes is characterized T_g to T_h ,. The contrast between the two arrangements is displayed in the accompanying condition:

$$A_{g \to h} = T_h \otimes T_g \tag{8}$$

This thought simply forces an irregular number $A_{g \to h}$ of developments inside the rundown of that is successful. Summation: on T_h off chance that be position and A be the rundown of developments, T_h + A method. A development list forces on vector that makes another situation in the space. So the relocation administrator is communicated as follows.

$$A_{g \to h} = P_{goalpo\text{int}} \otimes P_{currenthabitat} \quad (9)$$

$$P_{nexthabitat} = P_{currenthabitat} \oplus f \otimes A_{g \to h} \quad (10)$$

We get A on the $P_{currenthabitat}$ is applied. Rundown of movements for this model is as per the following.

$$A = P_{goalpo\text{int}} - P_{currenthabitat} = \{(2,3,4);(3,2,3);(6,4,3)\} \quad (11)$$

Forcing these developments on $P_{currenthabitat}$, in actuality produce $P_{goalpo\text{int}}$. In any case, in the cuckoo relocation in the MCO, just a level of the developments to $P_{currenthabitat}$ ought to be applied.

$$A' = \{(2,3,4);(3,2,3)\} \quad (12)$$

The impact of the MCO algorithm for feature selection in dance action recognition is profound, contributing to improved performance, dimensionality reduction, enhanced interpretability, and computational efficiency. By leveraging the algorithm's capabilities, researchers and practitioners can develop more accurate, efficient, and interpretable dance action recognition systems that better meet the demands of real-world applications.

3.3 Dance action recognition

Wavelet analysis decomposes dance video sequences into different frequency components, capturing both temporal dynamics and frequency characteristics. Wavelet transformation effectively represents subtle variations and patterns in dance movements, providing a rich feature space for classification. The wavelet neural network (WNN), wavelet transformation acts as a preprocessing step, extracting relevant temporal and frequency features from dance sequences. The neural network component processes the wavelet-transformed features, learning complex patterns and relationships inherent in dance actions. Arbitrary Woodland is a group gaining strategy that totals expectations from numerous choice trees. Random Forest (RF) ability to handle high-dimensional feature spaces and noisy data makes it well-suited for dance action recognition tasks. The WNN-RF model is trained using labeled dance video datasets, where each video is associated with specific action or movement label. Wavelet transformation pulls features from the video sequences during training. These features are then sent to the WNN for processing. The result of the WNN part fills in as contribution to the RF classifier, which figures out how to order dance activities in view of the extricated highlights. RF provides insights into feature importance, quantifying the contribution of each feature to the classification process. Feature importance scores generated by RF facilitate the interpretation of model decisions, highlighting the temporal and frequency characteristics that distinguish different dance actions. WNN-RF exhibits robustness against noise and variability in dance sequences, thanks to its ability to extract discriminative features across different frequency bands and temporal scales. WNN-RF classification can be parallelized and optimized for performance on large-scale dance datasets, making the model suitable for real-world applications.The persistent wavelet change requires numerous and creates extra data; thus, it dials back the investigation speed. Consequently, because of the computational weight of the approaching information, the discrete wavelet change with fast and precision is chosen for this model. The discrete wavelet change depends on the accompanying capability.

$$DWT(P,Q) = 2^{\left(-\frac{P}{2}\right)} \sum_{S=0}^{S-1} F(S)\phi\left(\frac{S}{2^P} - Q\right) \tag{13}$$

The first time series with F(s) and the mother wavelet with ϕ(S) have been communicated. Where m and n are the transmission and scaling boundaries, individually, both control the mother-frequency dislodging at the primary frequency and the wavelet extension, separately. The length of the whole time series is communicated by S. There are multiple ways of carrying out a discrete wavelet change; one of the most widely recognized strategies depends on the hypothesis of examination with numerous separations.

$$g = F(a) = F(w^{(1)}a + Y^{(1)}) \tag{14}$$

$$R = H(F(a)) = \hat{a} \tag{15}$$

$$\hat{a} = h(w^{(2)}g + Y^{(2)}) \tag{16}$$

As a matter of fact, the reason for preparing an autoencoder is to find the ideal worth of the loads and predispositions of the layers so the misfortune is limited. The calculation used to prepare an autoencoder brain network is mistake spread type and its learning is solo sort.

$$l(Y, H(F(A)) \tag{17}$$

where l is the misfortune capability, for example, the mean squared mistake which punishes the capability h(F(a)) because of the irregularity with a.

$$\rho_I = \frac{1}{Q} \sum_{J}^{Q} g^{(l)}(A_J) \tag{18}$$

Where q addresses the all out preparing information, l and Ja connect with the secret layer number and the J-th preparing input, additionally is the result of the I-th neuron. In the WNN-RF, a sort of wavelet enactment capability is utilized. WNN-RF comprises of four layers: input, two stowed away and yield layers. Numerical conditions are introduced beneath for CNN with a solitary secret layer.

$$u_P = \sum_{l} w_{Pl} J_l + \theta_P \tag{19}$$

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$$T_Q = \sum_P v_{QP} G_P + \gamma_Q \quad (20)$$

$$g_P = F_c(u_P) \quad (21)$$

where; w_{Pl} : The load between the info layer neuron and secret layer neuron m; θm: The predisposition an incentive for the secret layer neuron q, v_{QP} : The load between the secret layer neuron m and information layer neuron q; γ_q : The inclination an incentive for the result layer neuron q. The result an incentive for input layer neuron l; H_p and op.

$$\text{F(z)}=\psi_{mexhat} = (1 - XrEz^2)E^{-yrEz^2} + I(1 - XrEz^2)E^{-yrEz^2} \quad (22)$$

In this review, upsides of 0.1 and 2 have been decided for boundaries x and y, separately. The squared blunder capability has been liked as mistake capability. The quadratic mistake for the p design is determined as follows.

$$e_m = (1/2)\sum_{q=1}^{Q} | S_q - o_q |^2 = (1/2)\sum_{q=1}^{Q} | \delta^q |^2 \quad (23)$$

where Q is the quantity of neurons in the result layer. (δq = Sq − Oq), is the blunder between the real example oq and the objective example Sq of result neuron. WNN-RF displays strength to commotion and fluctuation present in video successions, which is essential for exact dance activity acknowledgment in genuine situations. The troupe idea of the irregular woodland part mitigates the impacts of commotion and exceptions in the information, while the versatile learning abilities of the wavelet brain network empower the model to adjust to varieties in dance developments across various entertainers, styles, and conditions.

4. Results and discussion

In this part, we present the outcomes and near examination of proposed and existing condition of workmanship dance activity acknowledgment models. To validate the performance of various dance action recognition models using dance video dataset which consists of 13,400 videos.Our proposed InceptionV3+MCO+WNN-RF model is implemented on Google collaboration environment with the python programming language. The results of our proposed InceptionV3+WNN-RF model are compared with the existing models such as DNN, RNN, LSTM, XGBoosting,ResNet, DenseNet50, Inception V3, 3D-CNN and CNN [31]. The results have validated through different measures such as accuracy, precision, recall, F1-score, and detection rate.

Table 1 Summary of dataset

Position	Number of samples		
	Training	Testing	Total
Head	1800	880	2680

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Left shoulder	1800	880	2680
Right shoulder	1800	880	2680
Left hand	1800	880	2680
Right hand	1800	880	2680
Total	9000	4400	13400

5.1 Dataset description

Table 1 describes the summary of dataset which is utilized for validating the performance of various dance action recognition models comprises a comprehensive collection of dance videos, totaling 13,400 samples. These samples are categorized based on different positions within the body, including the head, left shoulder, right shoulder, left hand, and right hand. There are training and testing samples for each position category, and the number of samples is set for each category. There are 1,800 training samples and 880 testing samples for each body position, for a total of 2,680 samples per position. So, the dataset has a total of 13,400 samples: 9,000 for training and 4,400 for testing. This is true for all body positions. The dataset includes a wide variety of dance moves, with 102 unique actions or gestures. The videos also have different lengths, ranging from 2.32 seconds to 67.32 seconds. This shows how different and complicated the dance sequences in the dataset are. This dataset has a lot of different dance videos, which gives you a lot of chances to test how well dance action recognition models work with different body positions and types of movement. The presence of both training and testing samples guarantees a thorough assessment and confirmation of the models' precision and generalization abilities. The test samples from the dataset are shown in Fig. 2.

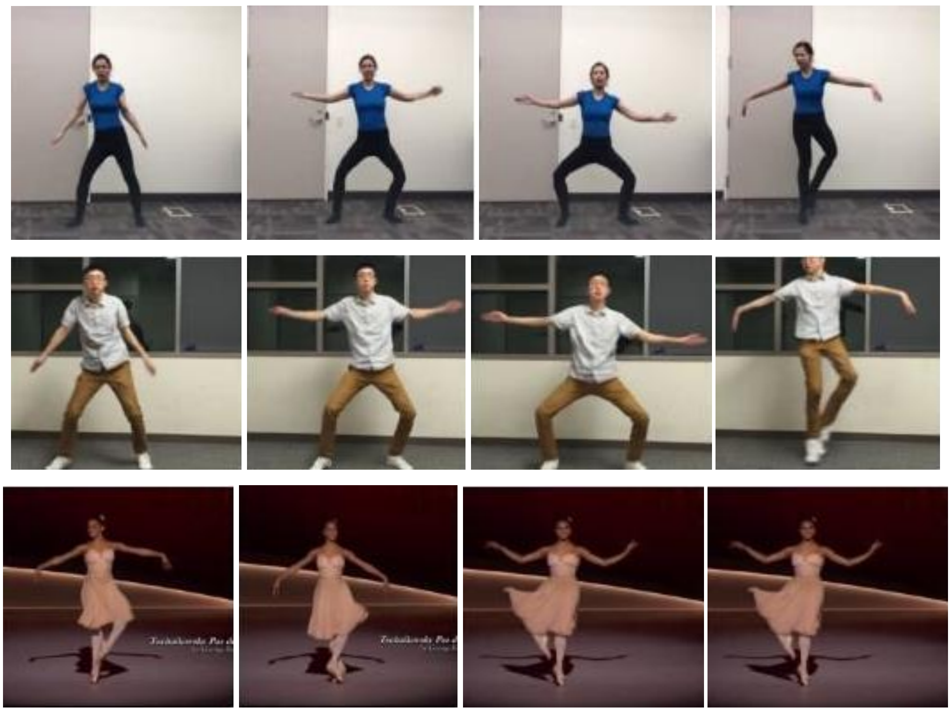

Fig. 2 Test samples from dataset

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5.2 Comparative analysis of proposed and existing models for dance action recognition

Table 2, which compares the accuracy of different dance action recognition models, shows how they did in different numbers of experiments, from 50 to 250. Each model's accuracy is measured as a percentage, indicating the proportion of correctly recognized dance actions out of the total number of actions. Beginning with the DNN model, its accuracy ranges from 44.499% to 44.589% across the different experiment counts. The RNN exhibits slightly higher accuracy, ranging from 50.395% to 50.485%. LSTM shows further improvement, with accuracy ranging from 56.291% to 56.381%. XGBoosting demonstrates even higher accuracy, ranging from 62.187% to 62.277%. Moving on to the CNN variants, ResNet achieves accuracy ranging from 68.083% to 68.173%, while DenseNet50 outperforms it slightly with accuracy ranging from 73.979% to 74.069%. Inception V3 exhibits higher accuracy, ranging from 79.875% to 79.965%. The 3D-CNN model further enhances accuracy, ranging from 85.771% to 85.861%.However, the significant improvement in accuracy is observed with the InceptionV3+WNN-RF model, which achieves remarkable accuracy ranging from 97.563% to 97.653%. This represents a substantial increase compared to the other models, shows the effectiveness of incorporating WNN-RF into the InceptionV3 architecture. Fig. 3 shows a progressive increase in accuracy across the different models, with each successive model building upon the strengths of its predecessors.

Table 2 Accuracy comparison

Dance action recognition model	Number of experiments				
	50	100	150	200	250
DNN	44.499	44.568	44.388	44.061	44.589
RNN	50.395	50.464	50.284	49.957	50.485
LSTM	56.291	56.360	56.180	55.853	56.381
XGBoosting	62.187	62.256	62.076	61.749	62.277
ResNet	68.083	68.152	67.972	67.645	68.173
DenseNet50	73.979	74.048	73.868	73.541	74.069
Inception V3	79.875	79.944	79.764	79.437	79.965
3D-CNN	85.771	85.840	85.660	85.333	85.861
CNN	91.667	91.736	91.556	91.229	91.757
InceptionV3+WNN-RF	97.563	97.632	97.452	97.125	97.653

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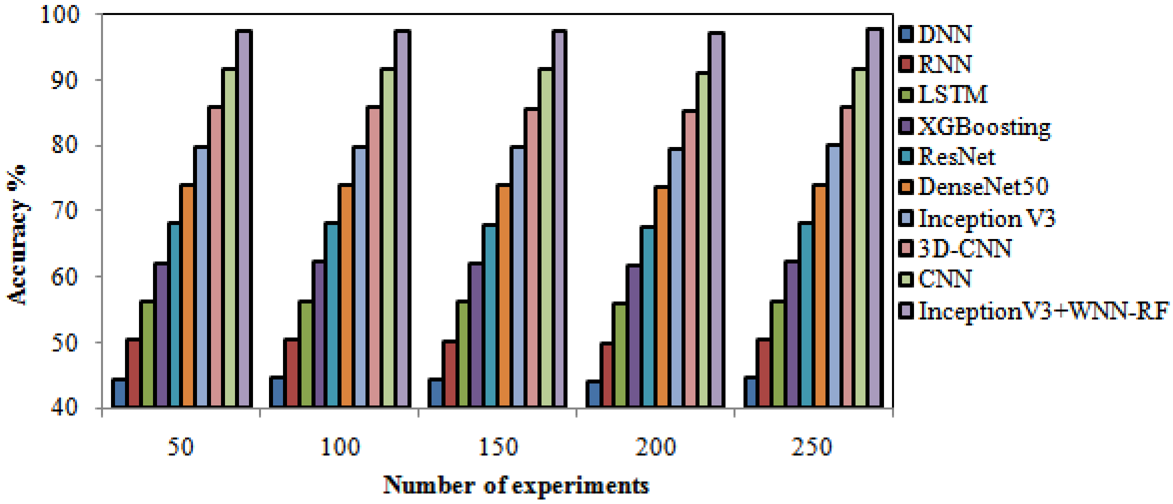

Fig. 3 Accuracy comparison of various models for dance action recognition

Table 3 presents the precision comparison of various dance action recognition models across different numbers of experiments, ranging from 50 to 250. Precision, in this context, refers to the proportion of correctly identified positive instances out of all instances that were predicted as positive by the model. Starting with the DNN model, its precision ranges from 31.591% to 31.224% across the different experiment counts. The RNN shows slightly higher precision, ranging from 38.576% to 38.209%. LSTM exhibits further improvement, with precision ranging from 45.561% to 45.194%. XGBoosting demonstrates higher precision, ranging from 52.546% to 52.179%. Moving on to the CNN variants, ResNet achieves precision ranging from 59.531% to 59.164%, while DenseNet50 slightly outperforms it with precision ranging from 66.516% to 66.149%. Inception V3 exhibits higher precision, ranging from 73.501% to 73.134%. The 3D-CNN model further enhances precision, ranging from 80.486% to 80.119%. However, the most significant improvement in precision is observed with the InceptionV3+WNN-RF model, which achieves remarkable precision ranging from 94.456% to 94.089%. This represents a substantial increase compared to the other models, showcasing the effectiveness of incorporating WNN-RF into the InceptionV3 architecture. Fig. 4 demonstrates a progressive increase in precision across the different models, with each successive model building upon the strengths of its predecessors.

Table 3 Precision comparison

Dance action recognition model	Number of experiments				
	50	100	150	200	250
DNN	31.591	31.709	31.393	31.452	31.224
RNN	38.576	38.694	38.378	38.437	38.209
LSTM	45.561	45.679	45.363	45.422	45.194
XGBoosting	52.546	52.664	52.348	52.407	52.179

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ResNet	59.531	59.649	59.333	59.392	59.164
DenseNet50	66.516	66.634	66.318	66.377	66.149
Inception V3	73.501	73.619	73.303	73.362	73.134
3D-CNN	80.486	80.604	80.288	80.347	80.119
CNN	87.471	87.589	87.273	87.332	87.104
InceptionV3+WNN-RF	94.456	94.574	94.258	94.317	94.089

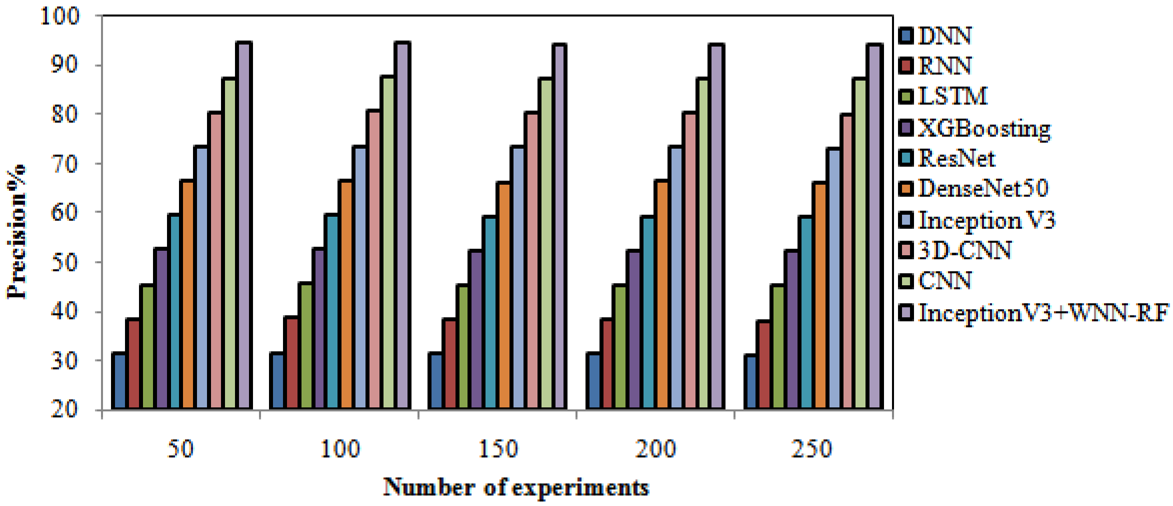

Fig. 4Precision comparison of various models for dance action recognition

Table 4 presents the recall comparison of different dance action recognition models across various numbers of experiments, ranging from 50 to 250. Recall, also known as sensitivity, measures the proportion of actual positive instances that were correctly identified by the model. Beginning with the DNN model, its recall ranges from 24.281% to 24.594% across the different experiment counts. The RNN exhibits slightly higher recall, ranging from 32.140% to 32.453%. LSTM shows further improvement, with recall ranging from 39.999% to 40.312%. XGBoosting demonstrates higher recall, ranging from 47.858% to 48.171%. Moving on to the CNN variants, ResNet achieves recall ranging from 55.717% to 56.030%, while DenseNet50 slightly outperforms it with recall ranging from 63.576% to 63.889%. Inception V3 exhibits higher recall, ranging from 71.435% to 71.748%. The 3D-CNN model further enhances recall, ranging from 79.294% to 79.607%. However, the most significant improvement in recall is observed with the InceptionV3+WNN-RF model, which achieves remarkable recall ranging from 95.012% to 95.325%. This represents a substantial increase compared to the other models, showcasing the effectiveness of incorporating WNN-RF into the InceptionV3 architecture. Fig. 5 demonstrates a progressive increase in recall across the different models, with each successive model building upon the strengths of its predecessors.

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Table 4 Recall comparison

Dance action recognition model	Number of experiments				
	50	100	150	200	250
DNN	24.281	24.726	23.837	24.125	24.594
RNN	32.140	32.585	31.696	31.984	32.453
LSTM	39.999	40.444	39.555	39.843	40.312
XGBoosting	47.858	48.303	47.414	47.702	48.171
ResNet	55.717	56.162	55.273	55.561	56.030
DenseNet50	63.576	64.021	63.132	63.420	63.889
Inception V3	71.435	71.880	70.991	71.279	71.748
3D-CNN	79.294	79.739	78.850	79.138	79.607
CNN	87.153	87.598	86.709	86.997	87.466
InceptionV3+WNN-RF	95.012	95.457	94.568	94.856	95.325

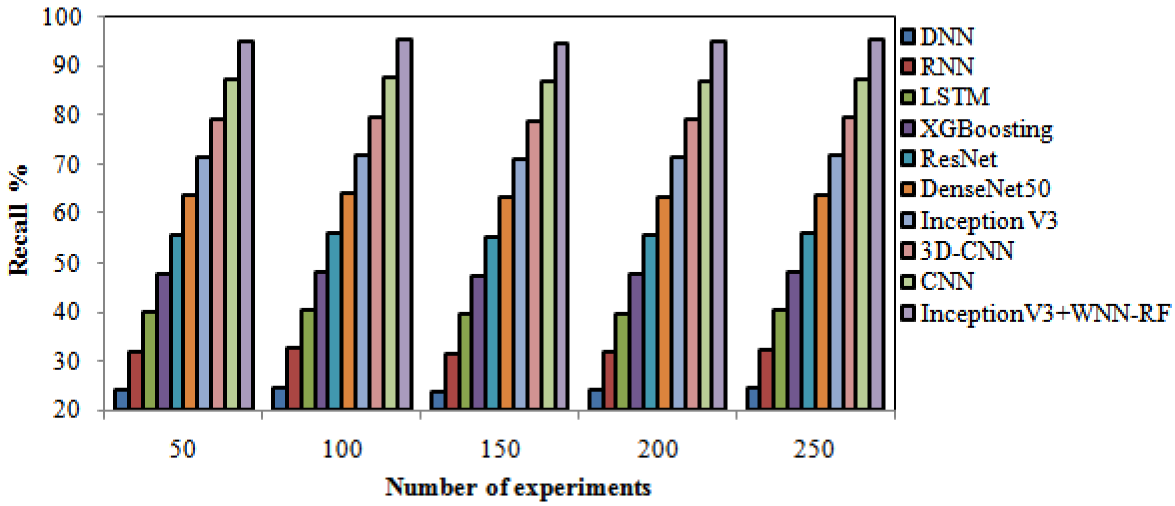

Fig. 5 Recall comparison of various models for dance action recognition

Table 5 illustrates the F1-score comparison of different dance action recognition models across various numbers of experiments, ranging from 50 to 250. The F1-score is a metric that balances both precision and recall, providing a single measure of a model's accuracy. Beginning with the DNN model, F1-score ranges from 27.458% to 27.515% across the different experiment counts. RNN exhibits higher F1-scores, ranging from 35.065% to 35.097%. LSTM shows further improvement, with F1-scores ranging from 42.599% to 42.614%. XGBoosting shows higher F1-scores, ranging from 50.093% to 50.095%.Moving on to the CNN variants, ResNet achieves F1-scores ranging from 57.561% to 57.554%, while DenseNet50 slightly outperforms it with F1-scores ranging from 65.013% to 64.999%. Inception V3 exhibits higher F1-scores, ranging from 72.453% to 72.434%. The 3D-CNN

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model further enhances F1-scores, ranging from 79.886% to 79.862%. However, the most significant improvement in F1-score is observed with the InceptionV3+WNN-RF model, which achieves F1-scores ranging from 94.733% to 94.703%. It represents an increase compared to the other models, shows the effectiveness of incorporating WNN-RF into the InceptionV3. Fig. 6 shows a progressive increase in F1-scores across the different models, with each successive model building upon the strengths of its predecessors.

Table 5 F1-score comparison

Dance action recognition model	Number of experiments				
	50	100	150	200	250
DNN	27.458	27.785	27.098	27.306	27.515
RNN	35.065	35.378	34.718	34.915	35.097
LSTM	42.599	42.902	42.260	42.450	42.614
XGBoosting	50.093	50.389	49.759	49.944	50.095
ResNet	57.561	57.853	57.231	57.413	57.554
DenseNet50	65.013	65.301	64.686	64.865	64.999
Inception V3	72.453	72.739	72.128	72.306	72.434
3D-CNN	79.886	80.169	79.563	79.738	79.862
CNN	87.312	87.593	86.990	87.164	87.285
InceptionV3+WNN-RF	94.733	95.013	94.413	94.586	94.703

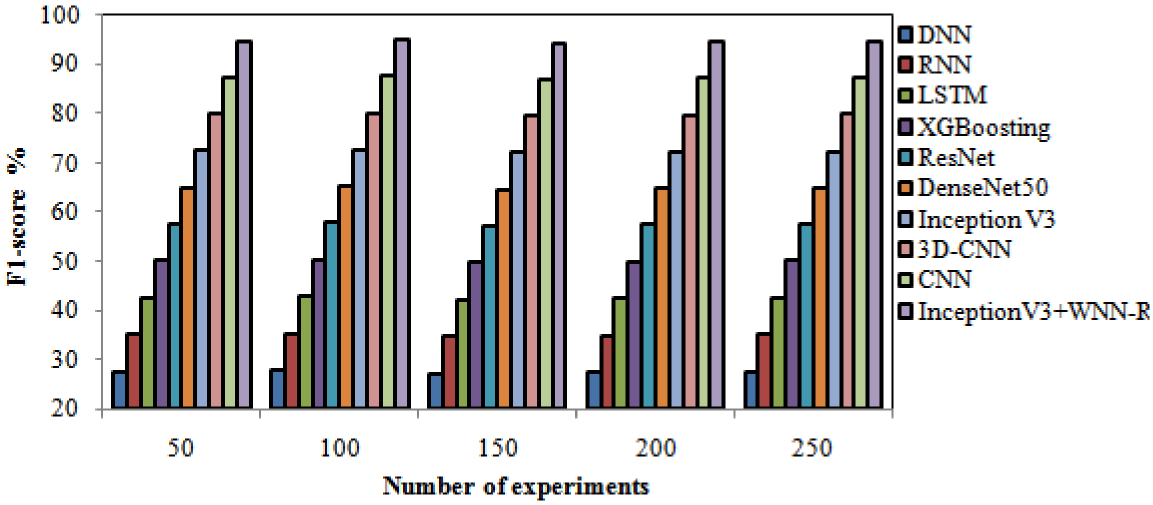

Fig. 6 F1-score comparison of various models for dance action recognition

Table 6 presents the recognition rate comparison of different dance action recognition models across various numbers of experiments, ranging from 50 to 250. The recognition rate reflects the percentage of correctly recognized dance actions out of the total number of actions. DNN

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model shows the recognition rate ranges from 35.978% to 36.052% across the different experiment counts. The RNN exhibits slightly higher recognition rates, ranging from 42.730% to 42.791%. LSTM shows further improvement, with recognition rates ranging from 49.445% to 49.497%. XGBoosting shows higher recognition rates, ranging from 56.140% to 56.186%. Moving on to the CNN variants, ResNet achieves recognition rates ranging from 62.822% to 62.864%, while DenseNet50 slightly outperforms it with recognition rates ranging from 69.496% to 69.534%. Inception V3 exhibits higher recognition rates, ranging from 76.164% to 76.200%. The 3D-CNN model further enhances recognition rates, ranging from 82.828% to 82.862%. However, the most significant improvement in recognition rate is observed with the InceptionV3+WNN-RF model, which achieves remarkable recognition rates ranging from 96.148% to 96.178%. It shows an increase compared to the other models, shows the effectiveness of incorporating WNN-RF into the InceptionV3 architecture. Fig. 7 shows a progressive increase in recognition rates across the different models, with each successive model building upon the strengths of its predecessors.

Table 6 Recognition rate comparison

Dance action recognition model	Number of experiments				
	50	100	150	200	250
DNN	35.978	36.177	35.743	35.683	36.052
RNN	42.730	42.921	42.501	42.436	42.791
LSTM	49.445	49.631	49.220	49.151	49.497
XGBoosting	56.140	56.323	55.917	55.846	56.186
ResNet	62.822	63.003	62.602	62.529	62.864
DenseNet50	69.496	69.675	69.277	69.203	69.534
Inception V3	76.164	76.342	75.946	75.871	76.200
3D-CNN	82.828	83.005	82.611	82.535	82.862
CNN	89.489	89.665	89.273	89.197	89.521
InceptionV3+WNN-RF	96.148	96.323	95.932	95.855	96.178

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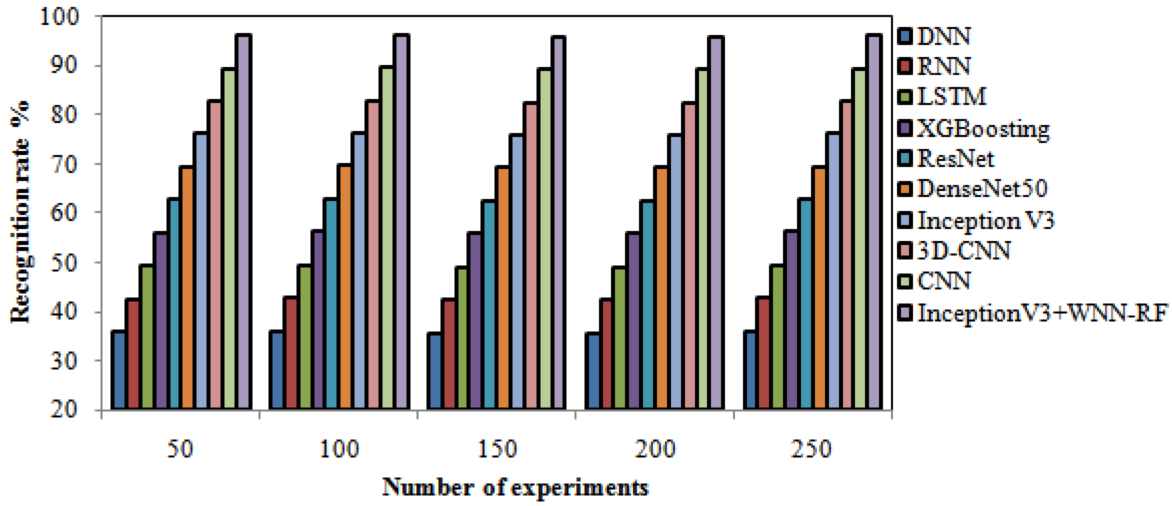

Fig. 7 Recognition ratecomparison of various models for dance action recognition

5. Conclusion

We propose an intelligent system for choreography design and rehearsal optimization, by a machine learning-based dance action recognition model. Initially, we employ the InceptionV3 architecture for feature extraction, extracting deep features from the spatial-temporal aspects of video data. Subsequently, we conduct optimal feature selection using the modified cuckoo optimization (MCO) algorithm, identifying the most relevant features from various options available. To achieve accurate dance action recognition from the video sequences, we leverage the wavelet neural network with random forest (WNN-RF) model. To evaluate the efficacy of our proposed InceptionV3+WNN-RF model and benchmark it against existing approaches, we perform experiments using a dataset comprising 13,400 dance videos. Our findings demonstrate the superior performance of the InceptionV3+WNN-RF model compared to other techniques. For example, while the CNN model, our closest competitor, achieves an accuracy of 91.667%, the InceptionV3+WNN-RF model achieves an accuracy of 97.485%. This represents a notable improvement of 5.896% over the CNN model. This enhancement underscores the effectiveness of the InceptionV3+WNN-RF model in accurately recognizing dance actions compared to existing methodologies.

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